Intelligent Gain-Scheduling for Robust Control of an Aerial Manipulator

Tariel Simonyan
National Polytechnic University of Armenia
Yerevan, Armenia
e-mail: simonyantariel07@gmail.com

Oleg Gasparyan
National Polytechnic University of Armenia
Yerevan, Armenia
e-mail: ogasparyan@gmail.com

***Abstract*—This paper addresses the robust control problem for an unmanned aerial vehicle (UAV) equipped with a 2-DOF robotic manipulator, designed for grasping and manipulating different payloads. The UAV-manipulator system experiences significant dynamic variations caused by manipulator movements and interactions with the payload, resulting in changes to the system's inertia matrix and displacements of the system's center of mass (CoM). To overcome this, we propose an intelligent gain-scheduled control approach that avoids online model computations. This is achieved by clustering the system's configuration space, with the optimal number of clusters. For each region, a local nominal inertia matrix is selected, and a PD controller is designed and tuned using a Genetic Algorithm (GA). Simulation results demonstrate that the proposed method improves the robustness and performance of the system across a wide range of configurations.**

***Keywords*—Unmanned aerial vehicle, robot manipulator, intelligent control system, gain-scheduling.**

I. INTRODUCTION

UAVs equipped with robotic manipulators, commonly referred to as aerial manipulators, have become a very popular research topic in the last decade. By combining aerial mobility with the ability of physical interaction with the world, these systems are offering a solution for hard-to-reach environment tasks. The aerial manipulators are used in diverse fields like military applications, photography and inspection, transportation, architecture, building, and construction [1].

However, aerial manipulators introduce a lot of challenges in system modelling and control. The dynamic coupling between UAV and manipulator introduces strong nonlinearities and time-varying dynamics. These variations, caused by manipulator movement and payload interactions, bring changes in the system's inertia matrix and displacements in CoM. These dynamic variations lead to a highly complex and non-robust control problem, making it hard to keep stable and precise control across the range of possible configurations and payloads.

To address this, researchers have proposed various robust and adaptive control methods. Sliding mode and H_∞ controllers have been used in handling bounded disturbances [2, 3], while neural network and backstepping approaches have been applied for variable inertia compensation and payload adaptation [4, 5]. Some works directly estimate the inertia matrix [6] or use adaptive observers for disturbance rejection [7].

Despite these advances, many existing methods require full symbolic modelling or real-time calculations of the dynamics. Traditional robust control approaches are often based on overly conservative global bounds for uncertainties, which can limit the system's performance and agility. Alternatively, methods that require real-time intensive computations are impractical for fast aerial manipulation tasks.

To overcome these limitations, we introduce an intelligent gain-scheduling control approach. Our method avoids online model computations by dividing the configuration space through clustering, where each region has its fixed local model and offline-tuned controller. The system's dynamics are linearized using approximate inverse dynamics [8], and the structured uncertainties are modelled by Linear Fractional Transformation (LFT) method [9]. For each local region, PD controllers are tuned using a GA to satisfy the robustness conditions [10].

The main contributions of this paper are:

- Linearization and uncertainty separation using approximate inverse dynamics.
- Intelligent configuration space clustering based on uncertainties.
- Region-based PD controller design via GA.
- Robustness verification using the Small Gain Theorem.

II. SYSTEM MODELLING AND PROBLEM FORMULATION

In this paper, we consider a quadrotor UAV with a 2-DOF planar manipulator attached below the UAV body, as shown in Fig. 1. To describe the system, two frames are considered: the inertial frame {I} and the body fixed frame {B}. The transformation between them is given by the rotation R_{IB} matrix, constructed from the UAV's Euler angles (roll, pitch, yaw) using a ZYX convention.

The UAV is modeled as a 6-DOF rigid body: with 3 translational coordinates and 3 rotational angles. The manipulator consists of two revolute joints that operate in the vertical plane beneath the UAV. The system is defined by six generalized coordinates:

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$$q = [z, \phi, \theta, \psi, \varepsilon_1, \varepsilon_2]^T, \quad (1)$$

where z is the UAV's height in the inertial coordinates, $\Omega = [\phi, \theta, \psi]^T$ denotes the UAV's Euler angles, and $\Upsilon = [\varepsilon_1, \varepsilon_2]^T$ are the joint variables of the robotic arm.

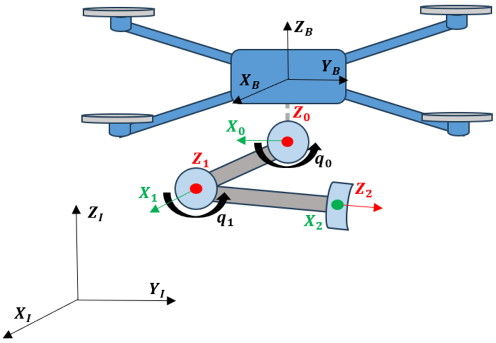

Fig. 1. UAV-manipulator system

The nonlinear coupled dynamics are derived using Euler-Lagrange formalism, resulting in the standard form [11]:

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau + \tau_D. \quad (2)$$

where $M(q)$ is R^{6x6} symmetric, positive-definite inertia matrix, $C(q,\dot{q})$ contains Coriolis and centrifugal terms, $G(q)$ is the gravity vector, τ is the generalized control inputs, and τ_D is the disturbance forces. For simplicity in notation, we set:

$$N(q,\dot{q}) = C(q,\dot{q})\dot{q} + G(q) - \tau_D, \quad (3)$$

thus, equation (2) can be rewritten as:

$$M(q)\ddot{q} + N(q,\dot{q}) = \tau. \quad (4)$$

This equation is linear in the control τ, and has full-rank $M(q)$, which can be inverted for any valid configuration. Taking the control τ as a function of the manipulator state in the form:

$$\tau = M(q)y + N(q,\dot{q}), \quad (5)$$

leads to the system described by

$$\ddot{q} = y \quad (6)$$

where y represents a virtual input vector [8].

This ideal linearization, however, requires online computation of the exact time-varying $M(q)$ and $N(q,\dot{q})$, which is computationally expensive, impractical, and in some cases impossible for real-time aerial manipulation tasks. To overcome this, we propose to use an offline computed fixed nominal model $(\widehat{M}, \widehat{N})$ in the inverse dynamics controller:

$$\tau = \widehat{M}(q)y + \widehat{N}(q,\dot{q}). \quad (7)$$

By introducing the nominal model into the inverse dynamics, the true dynamics can be separated into a nominal linear model (a double integrator) and structured nonlinear uncertainties, in the form:

$$\ddot{q} = y + \triangle_m y + \triangle_a, \quad (8)$$

where $\triangle_m$, $\triangle_a$ are multiplicative and additive uncertainties:

$$\triangle_m = M^{-1}(q)\widehat{M}(q) - I, \quad (9)$$

$$\triangle_a = M^{-1}(q)\widetilde{N}(q,\dot{q}), \quad (10)$$

$$\widetilde{N}(q,\dot{q}) = \widehat{N}(q,\dot{q}) - N(q,\dot{q}). \quad (11)$$

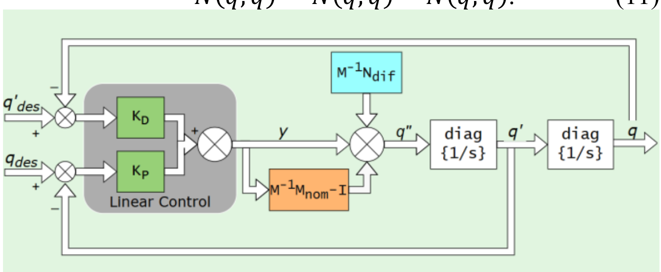

Fig. 2. Block diagram of the UAV-manipulator system

Fig. 2 shows the resulting interconnections of the double integrator plant and the structured multiplicative and additive uncertainties.

III. Controller Design

The proposed intelligent gain-scheduling strategy aims to design robust controllers for the UAV-manipulator system by partitioning its configuration space and tuning local controllers offline. This section describes the robust control framework, the configuration-space clustering method, and the AI-based PD controller tuning approach.

A. Small Gain Theorem

The structured uncertainties are modeled using the LFT framework for robustness analysis. As shown in Fig. 3, the feedback interconnection consists of a nominal generalized plant P and a block-diagonal uncertainty:

$$\triangle = \begin{bmatrix} \triangle_m & 0 \\ 0 & \triangle_a \end{bmatrix}. \quad (12)$$

The interconnection matrix $P(s)$ maps the uncertainty blocks (w_m from $\triangle_m$, w_a from $\triangle_a$) to their respective inputs (z_m, z_a) through the nominal closed-loop system. For our 6-DOF system with a diagonal plant $P_{plant}(s) = diag\{\frac{1}{s^2}, \dots, \frac{1}{s^2}\}$ and a diagonal PD controller $K(s) = diag\{K_1(s), \dots, K_6(s)\}$, where each $K_i(s) = K_{pi}(s) + K_{di}(s)/(\mathrm{T}s + 1)$, where T is the time constant for the derivative filter, interconnection matrix $P(s)$ is a 12x12 block matrix given by:

$$P(s) = \begin{pmatrix} -diag\left\{\frac{K(s)}{s^2+K(s)}\right\} & -diag\left\{\frac{K(s)}{s^2+K(s)}\right\} \\ diag\left\{\frac{1}{s^2+K(s)}\right\} & diag\left\{\frac{1}{s^2+K(s)}\right\} \end{pmatrix}. \quad (13)$$

For robustness analysis, we use the Small Gain Theorem [9], which provides a condition for robust stability in the presence of norm-bounded uncertainties. For our system, the stability is guaranteed if the supremum of the structured singular value $\mu_\Delta(P(jw))$ is less than 1 across all frequencies:

$$\sup_w \mu_\Delta(P(jw)) < 1. \quad (14)$$

Using the more conservative H_∞ norm product, robust stability is guaranteed if $\|P(s)\|_\infty \cdot \|\triangle\|_\infty < 1$. The robust stability margin (β) is defined as the inverse of this product:

$$\beta = \frac{1}{\|P(s)\|_\infty \cdot \|\triangle\|_\infty}. \quad (15)$$

For robust stability, the margin β should be greater than 1. However, directly applying this condition across the full configuration space is either infeasible or results in overly conservative bounds, as $\triangle$ can grow large in some configurations, for example, payload interactions.

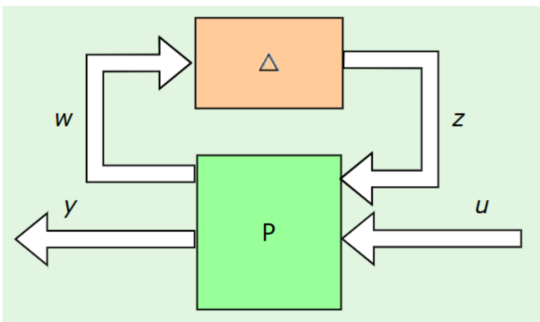

Fig. 3. LFT model of the system

To resolve this, we propose a strategy based on configuration-space partitioning. Instead of forcing a global robustness condition, we divide the space and apply the condition locally in each region. This method reduces uncertainty within each region and makes robust control design feasible. The next subsection details the clustering method used to achieve the partitioning.

B. *Configuration-Space Clustering*

To minimize the uncertainty in each region and make the small gain condition feasible without general conservatism, the configuration space is sampled across its possible ranges based on UAV states (Euler angles), manipulator joint angles $\varepsilon_1, \varepsilon_2$, and payload mass. For each sampled point, the H_∞-norm of the uncertainty $\triangle$ is evaluated by computing the deviation from a fixed local nominal $\widehat{M}, \widehat{N}$.

An AI-based clustering algorithm (K-Means) then divides the configuration space into regions with similar dynamic characteristics. A nominal inertia matrix $\widehat{M}$ is calculated offline for each cluster center.

The determination of the optimal number of clusters (K) is important for balancing uncertainty reduction against controller complexity. We employ the Elbow Method [12] to intelligently select K, with the following steps:

1. Running the K-Means algorithm for a range of K values.
2. Calculating the Sum of Squared Errors (SSE) for each K, which shows the compactness of clusters.
3. Plotting the SSE against K (Fig. 4). The "elbow" point in the curve, where the rate of decrease in SSE significantly slows down, indicates the optimal number of clusters.

For each region, precomputed bounds γ_i on the norm of $\triangle_i$ are used in the robustness condition.

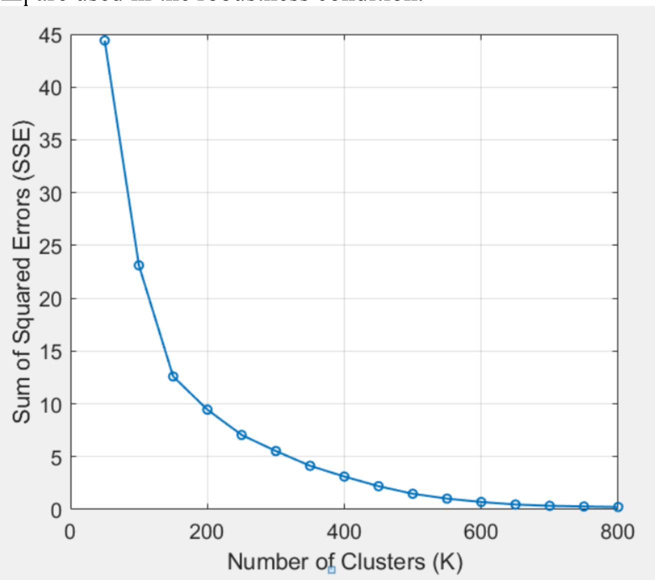

Fig. 4. Elbow method for optimal K

C. *Gain-Scheduled PD Controller*

In each clustered region of the configuration space, a local PD controller is designed as:

$$y = K_{pi}(q_{refi} - q_i) + \frac{K_{di}}{Ts+1}(\dot{q}_{refi} - \dot{q}_i). \quad (16)$$

To automate and optimize the PD gains K_p and K_d tuning process across all regions, we are using a GA-based approach. The GA finds the 12 gain parameters (6 K_p and 6 K_d) for each cluster by maximizing the reward function. The reward for each region is defined as:

$$R = -[\alpha_1 e + \alpha_2 \|\tau\|^2 + \alpha_3 \max(0, \|\triangle_i\|_\infty \|P(s)_i\|_\infty - 1)],$$

where e is the Root Mean Square Error (RMSE) of the step response, $\|\tau\|^2$ is the Integral of Squared Control Input (ISU), $\alpha_1, \alpha_2, \alpha_3$ are weighting coefficients.

Once trained offline, the GA provides optimal PD gains for each cluster. This gain schedule is then fixed and used during the runtime, avoiding online computations and ensuring robustness in each region.

IV. Simulation and Results

This chapter presents the simulation setup, the results obtained from applying the proposed intelligent gain-scheduling control approach, and a discussion of the system's performance and robustness.

Simulations were conducted in Matlab software to evaluate the performance and robustness of the UAV-manipulator system. The configuration space of the UAV-manipulator system, defined by its 6 generalized coordinates, was systematically sampled across its feasible range. The inertia matrix $M(q)$ for each sampled point was calculated using a detailed nonlinear dynamic model. Based on these characteristics, the configuration space was divided into K=300 distinct regions using the K-Means clustering algorithm.

For each clustered region, a local PD controller was designed. The controller coefficients were tuned offline using the GA method. The GA's objective function was designed to minimize the tracking error, control effort, and maximize the robustness margin. A derivative filter with a time constant of T=0.01 seconds was used in the PD controller to ensure proper implementation and noise reduction.

Fig. 5 illustrates the distribution of the uncertainty norms $\|\triangle_i\|_\infty$ across the sampled configuration space, color-coded by cluster. This localized bounding of uncertainty is fundamental to enabling the robust control design for each region, as it ensures that uncertainty within any given cluster is significantly smaller than a global bound would be.

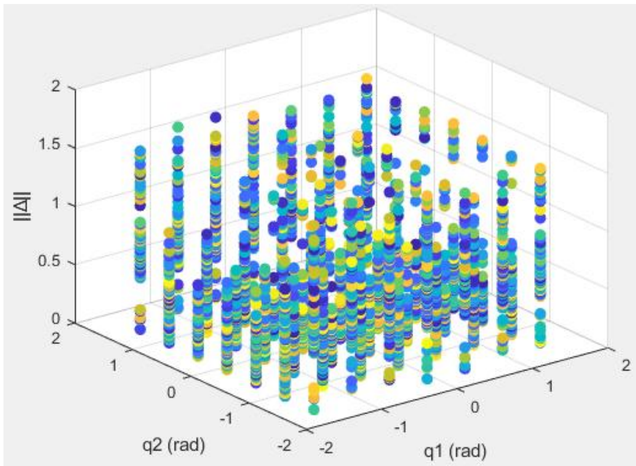

Fig. 5. Clustered uncertainty norms

A comparative analysis of the closed-loop step responses is shown in Fig. 6. The blue solid line represents the mean nominal step response of a single, globally tuned PD controller, while the red dashed line shows the mean nominal step response of the gain-scheduled PD controllers across all clusters. The gain-scheduled system exhibits a much faster rise time and settling time, with reduced overshoot, compared to the global controller. The better performance is a direct consequence of the localized tuning. This adaptability allows for maintaining high performance despite the time-varying dynamics of the UAV-manipulator system.

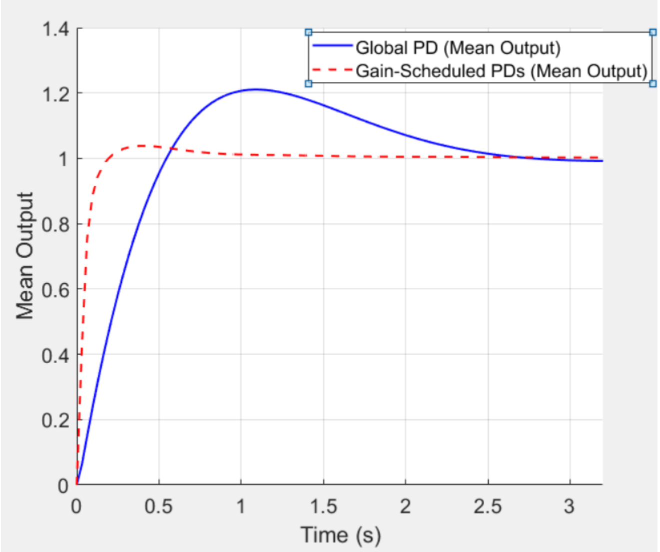

Fig. 6. Closed-loop step response comparison (mean output)

Fig. 7 is a validation of the robust stability achieved by GA-tuned controllers. The figure displays the robust stability margin (β) for each clustered region. As shown in the figure, the robust stability margin for all clustered regions is consistently above 1. This demonstrates that the GA successfully tuned the PD gains to satisfy the Small Gain Theorem. This result is a key achievement, as it confirms that the intelligent gain-scheduling approach effectively guarantees the stability of the UAV-manipulator system in the presence of its structured uncertainties across its entire operational envelope, without requiring overly conservative designs or online nonlinear model computations.

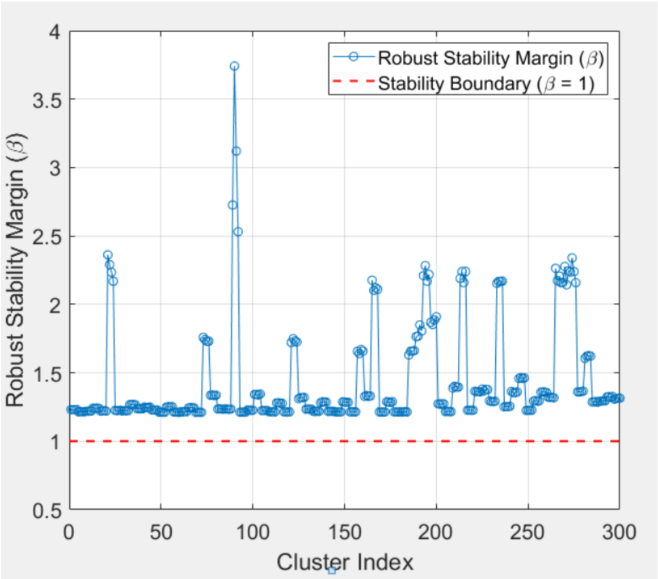

Fig. 7. Robust stability margin per cluster region

V. Conclusion

The simulation results collectively highlight the efficacy of the proposed intelligent gain-scheduling control strategy. By intelligently partitioning the configuration space and employing a GA for offline PD gain optimization, the system effectively addresses the challenges posed by UAV-manipulator dynamic coupling and time-varying inertia.

The clustering method successfully localizes the uncertainties, making robust control design feasible for each region. The GA-tuned controllers not only demonstrate superior performance but also satisfy the robust stability conditions across all identified operational regions. The method avoids the computational burden of online model computation, making it well-suited for real-world fast manipulation tasks.

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References

[1] J. Meng, J. Buzzatto, Y. Liu and M. Liarokapis, "On aerial robots with grasping and perching capabilities: A Comprehensive Review", *Frontiers in Robotics and AI*, vol. 8, pp. 1--24, Mar. 2022.

[2] Y. Chen et al., "Robust Control for Unmanned Aerial Manipulator Under Disturbances", *IEEE Access*, vol. 8, pp. 129869--129877, 2020.

[3] J. Morais, D. Cardoso, G. Raffo, "Robust optimal nonlinear control strategies for an aerial manipulator", *Congresso Brasileiro de Automática,* vol. 2, no. 1, 2020

[4] I.H. Imran, K. Wood, A. Montazeri, "Adaptive Control of Unmanned Aerial Vehicles with Varying Payload and Full Parametric Uncertainties", *Electronics*, vol. 13, no. 2, P. 347, 2024.

[5] E. Yilmaz, H. Zaki, M. Unel, "Nonlinear Adaptive Control of an Aerial Manipulation System" *18th European Control Conference (ECC)*, Naples, Italy, pp. 3916—3921, 2019.

[6] C. Park, A. Ramirez-Serrano, M. Bisheban, "Estimation of Time-Varying Inertia of Aerial Manipulators Performing Manipulation of Unknown Objects", *Proceedings of the 10th International Conference of Control Systems, and Robotics,* Niagara Falls, Canada, no. 209, pp. 1--8, 2023.

[7] H. Cao, Y. Li, C. Liu, S. Zhao, "ESO-Based Robust and High-Precision Tracking Control for Aerial Manipulation", *IEEE Transactions on Automation Science and Engineering*, vol. 21, no. 2, pp. 2139--2155, April 2024.

[8] B. Siciliano, L. Sciavicco, L. Villani, G. Oriolo, *Robotics: Modelling, Planning and Control*, Springer Publishing Company, Incorporated, 2010.

[9] K. Zhou, J. Doyle, *Essentials of Robust Control*, Prentice-Hall, Englewood Cliffs, NJ, 1998.

[10] Y. Ma, "Optimization of basic PID control algorithm based on genetic algorithm and Matlab", *Proceedings of the 3rd International Conference on Computing Innovation and Applied Physics,* vol. 30, pp. 178--186, 2024.

[11] S. Kim, S. Choi, H. J. Kim, "Aerial manipulation using a quadrotor with a two dof robotic arm", *Intelligent Robots and Systems (IROS), IEEE-RSJ International Conference on. IEEE*, pp. 4990--4995, 2013.

[12] E. Umargono, J. Suseno, S.K. Gunawan, "K-Means Clustering Optimization Using the Elbow Method and Early Centroid Determination Based on Mean and Median Formula", *Proceedings of the 2nd International Seminar on Science and Technology,* vol. 474, pp. 121--129, 2020.